Using a SOFM to learn Object Affordances

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Keywords :

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Abstract

Learning affordances can be defined as learning action potentials, i.e., learning that an object exhibiting certain "regularities" offers the possibility of performing a particular action. We propose a method to endow an agent with the capability of acquiring this knowledge by relating the object invariants with the potentiality of performing an action via interaction episodes with each object. We introduce a biologically inspired model to test this learning hypothesis and a set of experiments to check its validity in a Webots simulator with a Khepera robot in a simple environment. The experiment set aims to show the use of a GWR network to cluster the sensory input of the agent; furthermore, that the aforementioned algorithm for neural clustering can be used as a starting point to build agents that learn the relevant functional bindings between the cues in the environment and the internal needs of an agent.

Keywords: Ecological Perception, Learning, SOFM, Homeostasis.

1 Introduction

One of the main challenges for autonomous agents that have to survive in a changing and uncertain environment is to be able to make the right decisions in their interactions with the environment. This is the so-called *behaviour or action selection* problem, deciding "what to do next" (what behaviour to execute in a particular situation) to survive. The degree to which interactions will contribute to the agent's survival (to which these satisfy the agent's internal needs) will depend on the choice of a suitable object for the interaction.

Some proposed behaviour selection architectures make the agent's survival depend on their capability to maintain the stability of agent's *internal milieu* (survival related variables defining its needs), drawing on Ashby's notion of *viability* [1,5]. However, these architectures concentrate on the design of algorithms to select a behaviour according to the internal state of the agent, disregarding the state of the environment in their design considerations. In particular, apprehension of the appropriate functionalities of objects for one or another interaction has been overlooked, and information about the objects' potential for action has usually been hard-wired. Nevertheless, we argue that knowing the functionality of an object is also part of the adaptation problem.

Related to this, Gibson introduced the notion of *affordance* [7], which could be defined as the functionality an object offers to an agent. An affordance depends on the agent's morphology, on its abilities to interact and on the perception of the object. Therefore, the same set of affordances are only valid in the framework of a particular agent and environment. A first approach towards implementation was introduced in [3] with a very simple model that characterised the potentiality of performing certain actions to a set of objects via supervised learning; object features were perceived as a pattern to which to attach a value of appropriateness to perform an action. However, *affordances are held to be directly available from the environment, without the integration of perceived features into object representations* [2], affordances are based on the manner and flavour with which an agent perceives, on its own *invariants*.

In response to this idea, the architecture introduced in this paper aims at endowing the agent with the capability of building its own functional perception based on the invariants in the agent's environment, which the agent uses to decide to execute or not certain behaviour [6]. For example, we know that a table affords support, because it has a more or less flat surface at the right height whereon to sit. However, some large stones may also afford support. This example highlights the fact that to perform an action, the perception of certain regularities of each object in order to decide the right behaviour is fundamental. Therefore, we intend to use the agent's perceptual modalities (the agent's senses) to classify the regularities in the agent's sensory space and to match “sets of regularities” with “potentials of action”[1]. We suggest that this relation between perception and action is an implementation of Gibson's affordances.

We expect that affordances will extend the autonomy of the agent by providing the functional knowledge of the environment needed to guide the behaviour decision making, and hence to facilitate the agent's survival in an uncertain environment.

This paper is divided into several subsections: this introduction, a section to introduce related research issues, followed by subsection to present the Affordance Learning and Behaviour Selection Model. Then the section of experiments, which have been run to test our hypothesis with an autonomous agent in a simulated scenario. The goal is to show the different regularities perceived from different objects, and to test the aforementioned method to establish functional definitions of objects. The results and future endeavours are summarised in the last concluding subsection.

2 Related Work

The notion of affordance has been defined in the adaptive behaviour community as the notion that acts as a bridge between the perception of an object and the inference of the set of actions that the agent executes. Furthermore, this schema relating the action performance, the object and the agent has provided the necessary support for studying and reproducing imitative phenomena in artificial agents [4,10]. Affordances have also been brought back to the arena thanks to the neuroscientific research of Rizzolatti et al. [13], who recently demonstrated that some sets of neurons (mirror neurons) in the pre-motor cortex of some mammals exhibit the same activation pattern for the demonstrator as for the observer, making it possible for the learner to perform actions with objects she or he had never manipulated before. These neurons seem to mirror the perception and action pattern of the demonstrator in the learner, acting therefore as a bridge between the perception of the environment and the performance of a behaviour; that is, they seem to be part of the neural support for affordances.

Related to our work is the architecture of Guazzelli [8], who proposed a behaviour selection model to simulate the behaviour of rats navigating a T-maze that integrates drives and affordances for navigation. Nevertheless, in that case there was no learning; the affordances were already coded in and only related to navigation by interpreting affordance as the possibility of moving in one or another direction.

[1] Unlike Gibson's studies of the optical flow, we have to deal with other perceptual modalities (the agent's senses).

Furthermore, Cooper et al. [2] introduced a symbolic model of affordance learning by relating object features to action schemas. In their approach, object features are symbolically integrated into objects to bias one or another action, in analogous fashion to our previous schema [3]. We aim to bypass this feature-set to object integration via the use of a topological network (Self-Organising Feature Map ---SOFM). Related to this, Marsland et al. have recently introduced a topological network ---Growing When Required (GWR) [11], capable of clustering the regularities in the environment in an unsupervised manner.

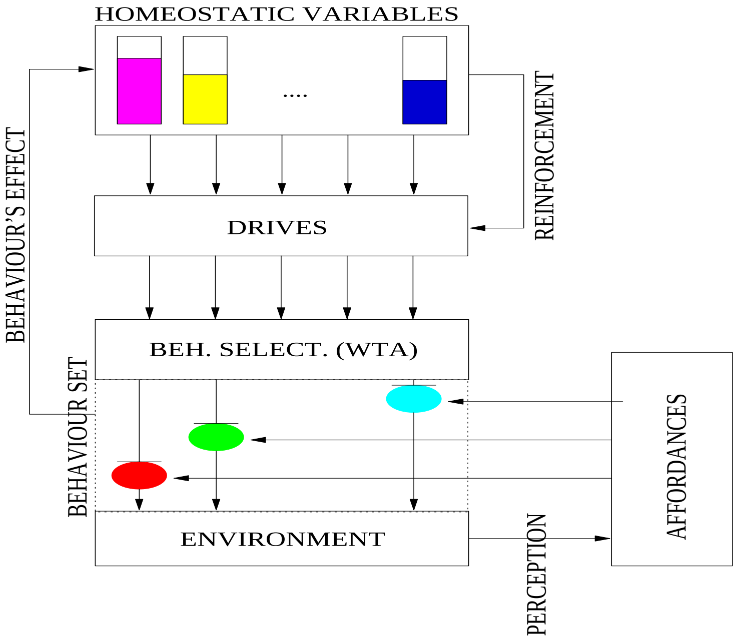

Figura 1: Affordance Learning and Behaviour Selection Model

3 Affordance Learning and Behaviour Selection Model

The model we introduce (refer to figure 1) aims at showing the possibility of learning affordances by relating the regularities (*invariants*) the agent perceives from an object at the moment of starting the execution of a behaviour with the success or failure of that interaction. We expect that if these interactions are performed repeatedly, patterns of success and failure will arise, relating the sensory regularities and the behaviour potential[2], building a causal relationship between them. We suggest that this set of relationships between the perceived regularities of the object and the possibility of performing a behaviour define the set of *affordances* of that particular agent in that particular scenario.

Furthermore, this knowledge endows the agent with the ability of anticipating the outcome of an interaction with some degree of certainty; hence, on the basis of this expectation, it can decide whether it is worth carrying out that action with that object or if it is preferable to search for an alternative. As shown by Cos-Aguilera et al. [3], using this ability results in a better adaptation to the environment and in a longer life span.

The model described below comprises several parts: a Perception Clustering Module to extract the patterns of regularities from the environment, an Architecture for Behaviour Selection to choose the behaviour to run next and a Learning Module to relate the active clusters with the outcome of each interaction.

3.1 Perception Clustering Module

[2] We have allowed ourselves to rephrase the concept of *action potential* for high level behaviours.

The first problem to face is the building of an appropriate neural representation of regularities in the environment of the robot. To this aim we have chosen to use biological inspiration and the simplest possible schema, according to Pfeifer's ecological point of view [12].

According to these criteria, a Growing When Required (GWR) network has been chosen [11]. This network has the advantage of dynamically adapting to the level of entropy of the environment (loosely speaking, to its level of variability) and of doing so in a Hebbian manner --- commonly used synapses are strengthened, conversely for the rarely triggered ones, which tend to fade and to disappear on a long-term basis. By following this procedure, the network's node-space adapts its topology to the sensory signal patterns. The representation therefore organises in sets of nodes ---clusters, which can be identified and numbered, matching the regularities of the environment, see figure 3. The network is 64 dimensional, and has as an input a 64-D vector of the level of illumination of the objects in the environment of the agent. Figures 4 and 5 show four sets of 2-D PCA projection of the sensory patterns together with the nodes of the SOFM matching the data.

This sort of network, unlike Kohonen networks [9], has the advantage of adapting their shape to the perception of the environment in a hebbian manner; hence, the most commonly perceived patterns will be represented by clusters with a higher amount of nodes, conversely for seldom encountered patterns.

The *parameters* of the network are: *activity* ($a_t = e^{-\|x_i - \omega_i\|^2}$), which is a function of the distance between ξ, the current sensory reading, and the position of node i (ω_i). Unlike for the original Marsland network, we calculate the square of the distance to obtain a normalising effect of the metric (nodes which are closer, near even more, and nodes which are apart, are considered to be further away). The second parameter is the *habituation threshold* h_t. This is a value signalling the limit of time we allow for a single node to place itself in the best fitting location; if more time is needed, it is considered that the node is not representing the data set sufficiently, hence a new node should be added. The third parameter is the *age* of each edge between nodes; edges connected to frequently used nodes are re-set to 0, conversely, a natural aging is experienced. Whenever the age of an edge surpasses the threshold is deleted. Nodes with no edges are also deleted. The final parameters are the *shifting coefficients* (ε_b) and (ε_n); which specify the dragging speed of the nodes towards the sample they are compared with.
To use a GWR works along the following lines:

1. The network is trained with a series of sensory patterns[3] to which it shall adapt its structure to. The adaptation algorithm compares each pattern to the node space of the network (measures the activity (a_t) of each node with respect to the sample). The first and second more active nodes are selected.
2. if the Euclidean distance between the closest node and the current interaction pattern is considered to be too far away, a new node is inserted and new bindings added; otherwise the closest node and the nodes at its neighbourhood are slightly dragged towards the input pattern, according to the next expression: $\Delta\omega_s = \varepsilon_b h_s (x_i - \omega_s)$ and $\Delta\omega_i = \varepsilon_n h_n (x_i - \omega_i)$, for the winning and direct neighbours, respectively ($0 < \varepsilon_n < \varepsilon_i < 1$). Nodes seldomly close to the input pattern are deleted. A fully detailed description of the GWR algorithm is provided by [11].

[3] A pattern is an instance of the input sensory signals.

3. Network exploitation. Once the network has been grown and its nodes identified, it can be exploited. This consists of identifying the closest node to the sensory input, and of attaching to the closest node a connecting weight to the behaviour just executed.

According to the Gibson's ecological approach, the perception of an animal is built in a functional manner by using the regularities of the optical flow to elucidate the action potentials of that situation (the affordances). In a very simple manner, the model the Perception Clustering Module introduces is the first step of a simple implementation of that view. This module can be identified within the figure of the complete model on the top-left side of figure 1.

3.2 Architecture for Behaviour Selection

This part of the architecture is a simplified version of that proposed in [1]. It consists of a set of homeostatic variables, survival-related internal variables that represent the internal resources of the agent, a set of drives that signal the need to compensate any homeostatic variable, a repertoire of behaviours and an arbitration mechanism to resolve conflicts among competing drives to choose the right behaviour. This architecture was fully described in [3].

The controlled homeostatic variables vary according to internal body dynamics and to the interactions of the agent with the environment. These are abstractions representing the internal resources that the agent has to keep under control to survive: nutrition, stamina and restlessness are the variables of our choice. Their values must be kept within the *viability zone* for the agent to remain alive; if their values overflow/underflow the upper/lower boundaries that define the variable's viability variable the robot dies. Furthermore, each homeostatic variable can have a status of “normality”, excess or deficit. Homeostatic variables have a dual behaviour; while there is no successful interaction with the environment, they behave monotonically, either with an increasing (restlessness) or a decreasing (nutrition, stamina) tendency, depending on their nature.

The drives are also abstractions that denote the urges for action based on the need to compensate a bodily need. When that need is detected, an appropriate mechanism of compensation is triggered. The drives monitor the levels of the homeostatic variables and initiate a process of compensation whenever they are in a deficit state. In our case, the mechanism of compensation is the selection and execution of a behaviour, that can solely be successfully executed if an appropriate object is nearby. In our schema, we have used three different drives: hunger (which controls nutrition), fatigue (controlling stamina), and curiosity (controlling restlessness). At each time step, each drive is assigned an intensity proportional to the magnitude of the error of its controlled variable.

The behaviours are coarse grained, and include a subset of actions. In this study to grasp, to shelter and to interact have been the chosen behaviours. The execution of the behaviour results in an interaction with an object in the environment that may reflect a compensation of the error for the most critical internal variable; contributing therefore to compensate the drives. In the general case, different behaviours can contribute to compensate a drive, but in our simplified model each drive can be satisfied by one behaviour only, “eat” (grasp an object) satisfies hunger, “shelter” satisfies fatigue, and “interact” satisfies curiosity.

The arbitration mechanism for behaviour selection follows a winner-take-all policy, using the drive that exhibits the highest urgency (the one with the highest level) to choose the behaviour to execute next. In our simplified model this is very easy because there is a single behaviour that can satisfy each drive.

Unlike for the model introduced in [3], we have further introduced two *Hormones*: Frustration and Satisfaction, that are respectively triggered when the outcome of an interaction episode with an object is successful or failed. Therefore, *hormones indicate the success or failure of an interaction*, which is used as an attentional (triggering) mechanism to learn that the particular object the agent interacted with, has or lacks the functionality it just attempted to perform. The values of the hormones are 1, if they are active, and 0 otherwise. They are represented in the centre of figure 1.

3.3 The Learning Mechanism

The problem posed consists of learning via interaction with the environment ---with the objects it contains--- to relate the perceived regularities to the possibility of performing one or more actions. Thus, the proposed method of learning is as follows:

- Everytime the agent detects an object, the closest node in the state space is identified. Figures 4 and 5 show the topologies representing the objects contained in the Khepera world used for simulation (x-axis represents the size and y-axis the shape of the object).
- In case the interaction succeeds, the hormone satisfaction will be released, conversely, it will be the hormone frustration. The release of one or another hormone indicates to the algorithm that fills in the table of results the positive or negative significance of the event, respectively, and whether to increment or decrement the value in the table related to the active (perceived) nodes and the executed behaviour (0.1 and -0.1 are the used increments).
- The learning results in a set of weights relating each node in the sensory space to each behaviour, signalling therefore the potentiality of performing that behaviour whenever the agent is facing a particular object.

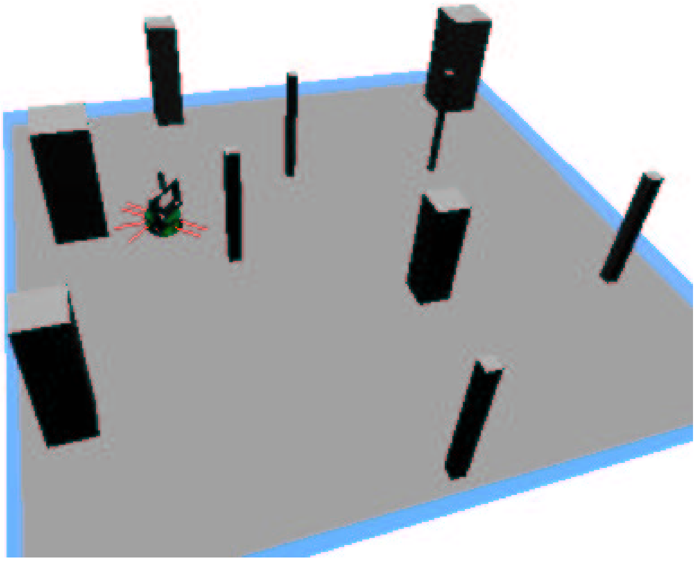

Figura 2: Simulated Khepera Environment

This learning procedure is called one-step backup reinforcement [14]. Several interaction episodes happen repeatedly throughout the duration of the simulation. The values are normalised after the end of the simulation; values close to 1.0 for a certain cluster and behaviour would mean that the behaviour is likely to be successful with that object, and the opposite if it is close to -1.0. These values measure the matching between the cluster (the regularity in the environment) and the behaviour potentials in an analogous fashion to a normalised probability value between -1.0 and 1.0.

4 Experiments and Results

The goal of the first experiment set is to demonstrate that artificial agents can learn to relate the invariants of the objects in the environment (clusters in the GWR) with the outcome of goal-oriented interactions. This would be analogous, loosely speaking, to learning to select appropriate objects (or the equivalent set of regularities) to successfully perform an interaction[4].

4.1 The Environment

A single environment, c.f. figure 2, has been chosen to show the applicability of the learning method mentioned above. A set of nine different objects have been placed in different locations of a simulated environment. The chosen objects are octahedral, from relative side sizes ranging between 0.08 and 0.01. The size of the arena is 0.5 x 0.5 units.

4.2 The Method

The method proposed to learn the affordances has been sub-divided into two phases; a clustering phase and an exploitation phase. Each phase is explained to follow on a step-by-step fashion.

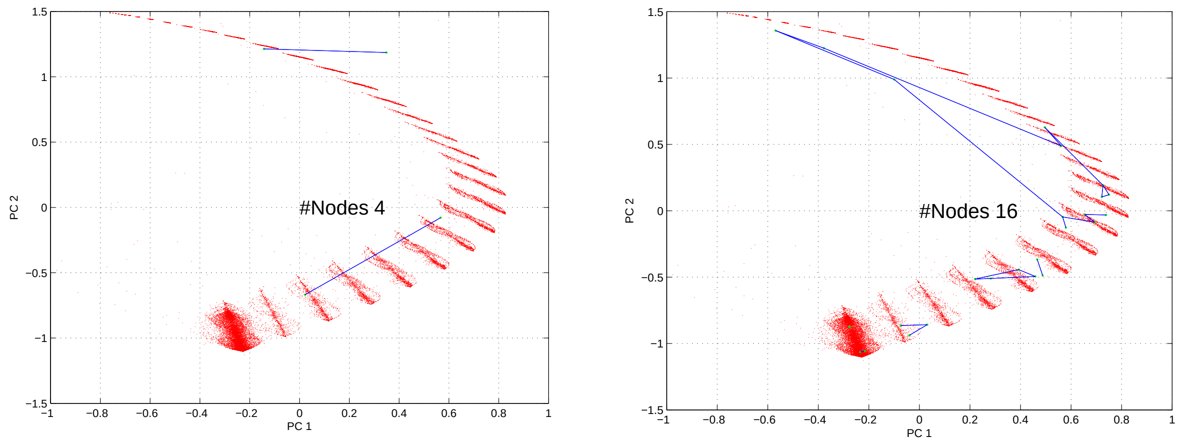

Figura 3: First 2 Principal Components of a Growing Neural Gas Network at its initial and final growing stage, left and right, respectively. The network (the dots bound by the edges) overlaps the sensory data (the cloud of fine dots).

Clustering Phase

1 The robot is placed in the environment. By following a random selection policy, it wanders around in the environment, interacting with the different objects, and building the GWR on the basis of a 64-D horizontal illumination vector of visual information, extracted from the objects in the environment with the camera.

2 Everytime an object is encountered, the object is centered, and always at the same distance, a snapshot of the object is taken.

3 The from object is extracted from the image, and reduced to a single 64-D vector. Thus objects in the environment have vertical symmetry, the horizontal vectors the image is composed of, are the same. Hence, we can choose to use a single vector without any loss of information about the object.

4 This vector is used to feed the GWR network. The parameters used for the network are: $energy = 0.5$, $\varepsilon_b = 0.5$, $\varepsilon_n = 0.006$, $a_{\max} = 50$. The final clustering of the environment together with the nodes representing them, are introduced in the sequence of figure 3. From left

[4] By successful we mean the interaction compensating the agent's internal deficits.

to right, we can see a 2-D Principal Component Analysis (PCA) representation of the samples of visual information, and of the corresponding SOFM fitting them.

5 The second phase is started whenever the structure of the network is stable.

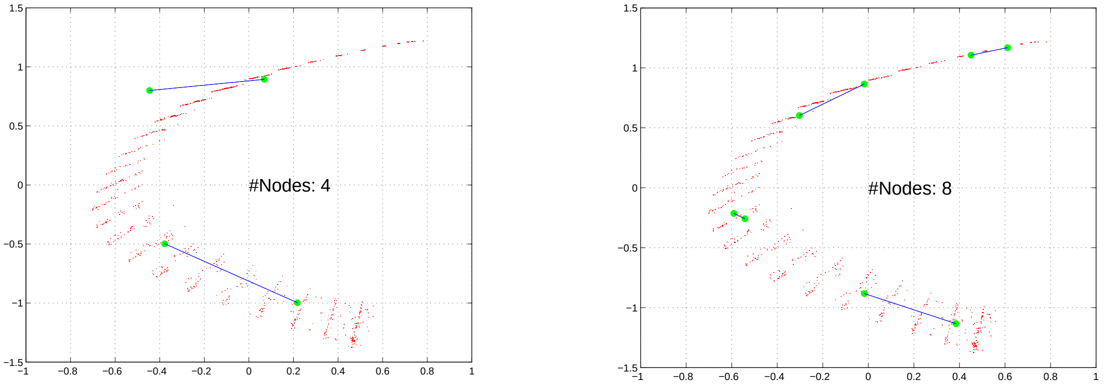

Figura 4: 2D-PCA with GWR overlapping with 4 and 8 nodes, left and right, respectively.

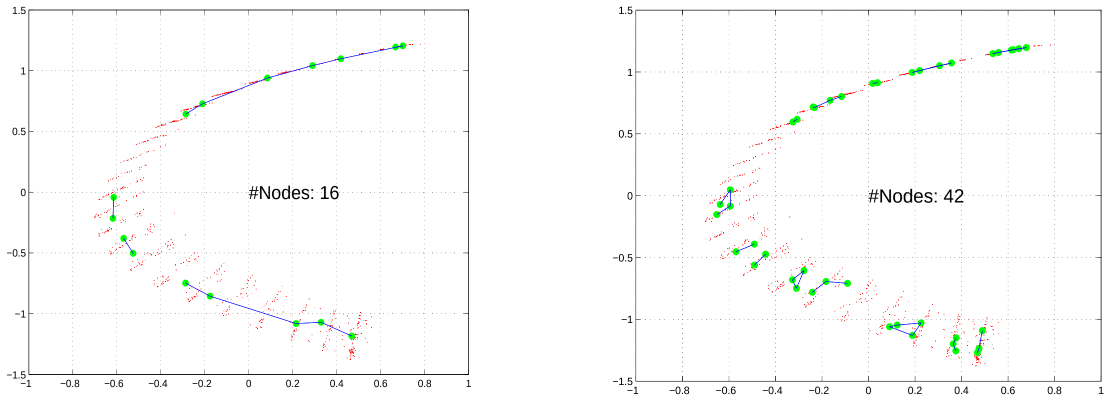

Figura 5: 2D-PCA with GWR overlapping with 15 and 42 nodes, left and right, respectively.

Exploitation Phase

1 The homeostatic variables of the agent are initialised to their optimal value. Table 1 shows the exponential decay parameters for each homeostatic variable (τ) and their optimal values. They all range between 0.0 and 1.0.

2 The behaviour to execute next is decided on the basis of the highest drive at the end of each interaction episode. Each of the drives is hard-wired to a behaviour, “hunger” to grasp (eat), “fatigue” to stamina and to “touch” (make contact) to curiosity, respectively.

3 Once an object is encountered, its closest node in the neural representation (GWR) is identified.

4 The behaviour is carried out. If the object is appropriate (affords that behaviour), the interaction will be successful, otherwise it will fail. In the former case, the homeostatic variable related to the performed behaviour varies towards its compensation, in the latter, it has no effect on the motivations[5].

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[5] Unlike for the first set of experiments published in [3], where a negative outcome implied a negative impact on the level of the homeostatic variables.

5 Furthermore, if it succeeds, the hormone satisfactions signals a 1, conversely the hormone frustration is triggered to the same value.

6 A set of weights, relating each node to each behaviour are updated at the end of each interaction. For the node perceived as active during the interaction (in our case it will be only one at a time) and for the behaviour currently run, an increment of 0.1 is given to the weight connecting node to behaviour. Conversely, it is decremented by -0.1. Positive increments are related to the activation of the hormone satisfaction and negative to the hormone frustration.

Name	**Tendency**	τ	**Optimal Values**
Nutrition	Decreasing	1E-5	0.9
Stamina	Decreasing	1E-5	0.8
Restlessness	Decreasing	1E-5	0.1

Tabla 1: Internal Milieu Values.

The same sequence, for training and for exploitation has been performed with four different networks 32, 16, 8 and 4 nodes have been used (c.f. figures 4 and 5).

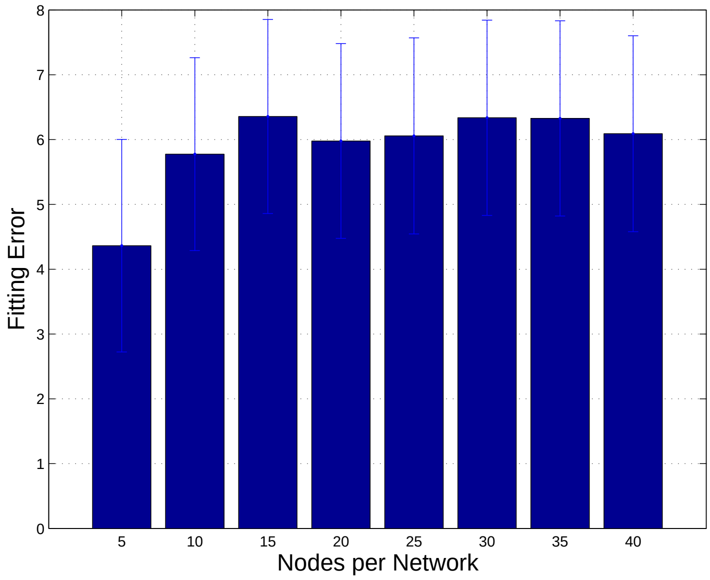

Figura 6: Number of Nodes vs. Accuracy.

4.3 Results

Four series of five simulations each have been run with each network in order to test the learning of the weights connecting each node to the behaviours. The results are shown in histograms in figures 7 and 8. X-axis is the node id for each network, and y-axis the affordance value, mediated over five simulations and ranging from -1 to 1, obtained through simulation. The two programmed affordances here are shelter and grasp. The relationship between the size of the objects and the morphology of the agent is only given via physical interaction in the latter case, for which the width of the gripper is the physical boundary to grasp or not an object. Conversely, the boundary to succeed in sheltering has been simulated; if the diameter of the base of the object is larger than a certain threshold, the object affords shelter. This reflects in the histograms; the nodes that afford shelter are, in fact, the ones representing the largest objects.

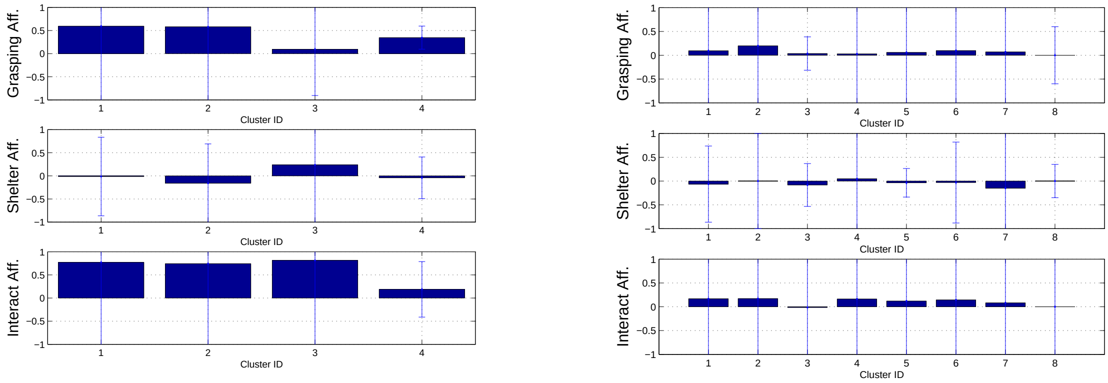

Figura 6: Learnt affordance values for behaviours grasp, shelter and touch/interact--- (top-down) for GWR with 4 and 8 nodes, left and right, respectively.

Furthermore, if the threshold of shelter is set appropriately, we can assume that large objects afford shelter and small objects afford grasping. This roughly reflects on figure 7, which suggests their sufficient level of representativity for the environment.

However, the GWR has also some representation limitations, thus there are some nodes, whose affordance is unclear. This means that they are representing objects whose size is, close to the width of the gripper for the case of grasping, and close to the shelter threshold for the case of shelter.

In general terms, these results confirm the expectation, thus we can appreciate that for networks with a larger amount of nodes than 16, the precision of the estimation is acceptable. The criterion to say so consists of examining the mean and variance of the affordance values obtained for each node. For the networks networks in figures 7, the mean and the variance values for most of the nodes are either larger than 0 or smaller, but they do not cross this threshold. This confirms that the interaction episodes with objects in the environment represented by these nodes are, with a certain degree of reliability, resulting in the same outcome. This does not happen for the networks with 4 and 8 nodes. Figure 5 shows the accuracy vs. number of nodes obtained by measuring the euclidean distance between each of the network nodes to 2000 snapshots of the objects in the environment. The affordance of touching (the third graph in the aforementioned depictions) is always positive, thus all objects afford to be touched.

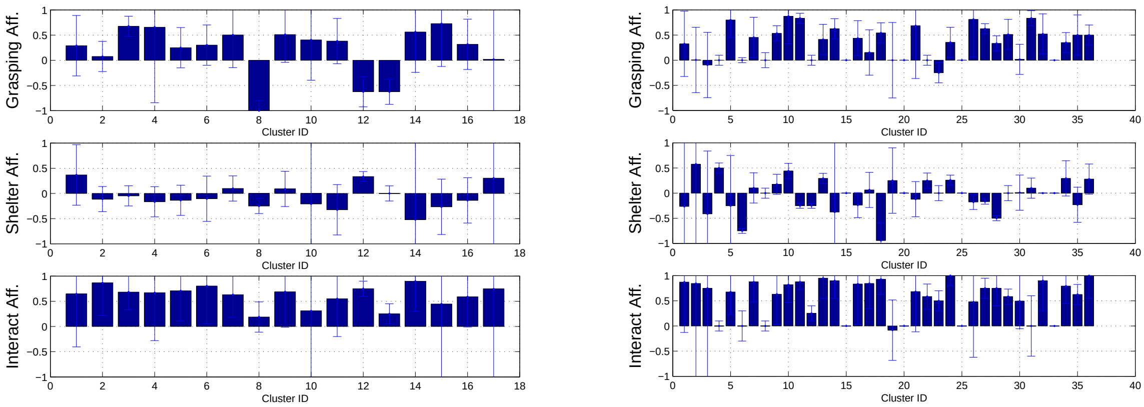

Figura 7: Learnt affordance values for behaviours grasp, shelter and touch (top-down) for GWR with 16 and 32 nodes, left and right, respectively.

This experiment suggests that GWR is a flexible representation that may be extended in real time to add nodes when required and the learning mechanism appropriate to these particular objects and simple environments. Furthermore, the case of the border nodes, whose affordances are not well define, suggests that depending on the degree of vicinity of the new node to the previous ones, it shall be possible to infer the affordances of the new cluster with a good degree of accuracy.

5 Conclusions and Future Work

The results obtained in the two experiment sets have been run according to an extended view of Gibson's ecological perception with a simulated agent. This suggests, that the GWR may be sufficient to identify the invariants of the objects in the environment, and that one-step backup reinforcement is sufficient to learn the potentiality of executing each behaviour within the repertoire of the agent.

This fact also highlights that affordances, while respecting its traditional definition: *the functionality an object affords to an agent*, could also be re-defined as follows: *the relationship between the regularities in the sensory flow*[6] *of an agent and the action potentials these offer to that particular agent*. This contains not only the functional view of an affordance, but also the learning procedure agents may use, and according to Gibson, the way evolution endowed an agent with the capability to adapt to its environment. In fact, the form of an animal depends on its environment, which modifies during its lifetime due to this dual relationship. The animal exploits the environment to satisfy its internal goals, and the environment, being never static, obliges the animal to continuously modify its behaviour patterns to adapt to the new situation to remain alive, e.g., the progressive depletion of water from a region may oblige the agent to walk longer distances or to modify its physiology to require less water.

According to the definition given above, affordances seem a sensible way to process sensory information, to ground the right environmental representation with the right behaviour and therefore to maintain the *internal milieu* within the agent's viability zone. We also argue that affordances, at least partly, are invariant based; several studies in neuroscience support examples of invariants used by some animals to detect the significant elements in the environment.

Nevertheless, we wish to stress the fact that affordances are task-, environment- and agent related. Hence, to be able to learn and use affordances, it is necessary to define the aforemenentioned framework. Each affordance will then depend on the morphology of the agent, on its set of internal goals and behaviours. This specificity can be optimised by using the appropriate sensory processing, such that reliably detects the necessary cues, adapting to the required level of discrimination of the behaviours to the level of complexity of the environment. However, to learn them, the execution of a behaviour must reflect on the internal goals of the agent. If the object or the required cues in the environment are matched, the effect must be considered positive, conversely negative. Therefore, only the affordances whose related cues are detectable and whose effect can be measured by the agent will be learnable, i.e., only these will constitute the set of affordances of that particular agent in that particular scenario.

Future experiments will address contemporary the fitting of the topology of the GWR to the environment with the assignment of affordance weights to the behaviour repertoire of the agent. Furthermore, the use of the camera in an environment with a single illumination point situated far above the centre of the environment, restricts the perception of the objects to their size (the edges are not detectable); being orientation independent. This often provokes imprecisions in the manipulation and a slight unreliability in the interaction outcomes. Hence, we intend to include orientation as a factor to perceive the objects in future experiments and to compare this procedure to other behaviour-based algorithms for object recognition.

[6] Sequence of sensory patterns perceived by an agent.

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